Artificial Intelligence

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Transient Identification & Operator Decision Support System for PHWR (Diagnostic System)

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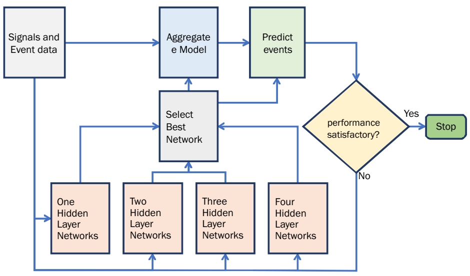

Schematic diagram of ANN approach

ABSTRACT

Artificial intelligence based transient identification and operator decision support system for 220MWe Pressurized Heavy Water Reactors (PHWRs) is developed and tested on a high speed computing facility at RSD, BARC. The transient identification module of diagnostic system employs Artificial Neural Network (ANN) model trained by a large database of plant transients simulated via core (RELAP5) and containment (CONTRAN) thermal-hydraulic code. The best-performing neural network model selection framework has been implemented in several stages with a highly random selection in the intial stage through the evolution of robust and efficient network in the final stage via recursive training scheme. The final ANN model has been obtained by creating an ensemble of the best-performing networks for identification of Loss of Coolant Accident (LOCA) and Main Steam Line Break (MSLB) scenarios. Blind validation exercises carried out on the best-performing models demonstrates thorough validation and testing of ANN models. The current version of Diagnostic system is capable of identifying a wide range of LOCA and MSLB scenarios in standard 220MWe PHWRs. Diagnostic system is built on a Remote Method Invocation (RMI) protocol concept for communication and integration of remote servers from the field (e.g. integration of Computerized Operator Information System (COIS)) for real-time transient identification.

KEYWORDS: *Operator decision support system, Diagnostic system, Neural networks, Nuclear power plant*

Introduction

Nuclear power plant (NPP) houses complex systems that are operated and monitored by human operators. When a transient occurs in the NPP (e.g. LOCA or MSLB), operator has to carry out diagnostic and corrective actions based on the available alarms/annunciations. Depending on the severity of the transient, readings of the instruments' may not always provide a clear indication of an anomaly at its incipient stage to the operator. In order to assist operator during such circumstances and to take timely corrective action, an Artificial Intelligence (AI) technique is useful. In view of this, development of AI based transient identification and operator decision support system (Diagnostic system) is the prime objective for accident management. The objective of the diagnostic system in any potentially unsafe scenario is to provide the operator suitable information about the evolving transients in terms of intensity of break in Primary Heat Transport (PHT) system, location of the break, etc. Transient identification is a decision making process based on a number of process parameters/alarm states in order to avoid/minimize the consequences associated with the specific transients. Analysis of an event/transient involve determination of the consequence of a specified event such as LOCA in terms of fuel temperature, PHT storage tank level, containment temperature and pressure, etc. Diagnosis is the identification of transients from the process signals selected from COIS. The event identification can be classified as a pattern recognition problem[1]. By properly selecting the plant parameters, a specific event can be identified by observing values/ variations of the relevant parameters. For this purpose, around 45 COIS signals have been selected from respective Emergency Operating Procedures (EOPs) for identifying LOCA and MSLB scenarios in PHWRs. The time-dependent transient data pertaining to the reactor core and the PHT has been generated using RELAP5[2] and CONTRAN[3] thermal hydraulic codes. There are a number of linear and non-linear pattern recognition techniques available in the literature[4]. However, ANN is one of the most widely employed machine learning techniques for solving such complex problems which involve a large number of input signals and output events. General characteristic of a neural network is the ability that quickly recognizes the various conditions or states of a complex system once it has been fully trained. The final ANN model has been integrated with Diagnostic system which provides most suitable information about the evolving transient and assists the operator to take corrective actions to mitigate the accident condition. The current version of the Diagnostic system is able to identify 33 LOCA and 18 MSLB scenarios in 220MWe PHWRs.

Simulation of LOCA and MSLB

PHT system depressurizes rapidly upon the occurrence of large breaks in PHT system thereby causing voids in the reactor core. This coolant voiding in the core causes positive reactivity addition and consequent power rise of reactor. Several trip signals will be activated namely high log rate, low PHT pressure, high neutron power, low PHT coolant flow and high reactor building pressure, etc. one after another in a short time. The sequence of trip actuation is largely dependent upon break location. In general, for breaks at Reactor Inlet Header

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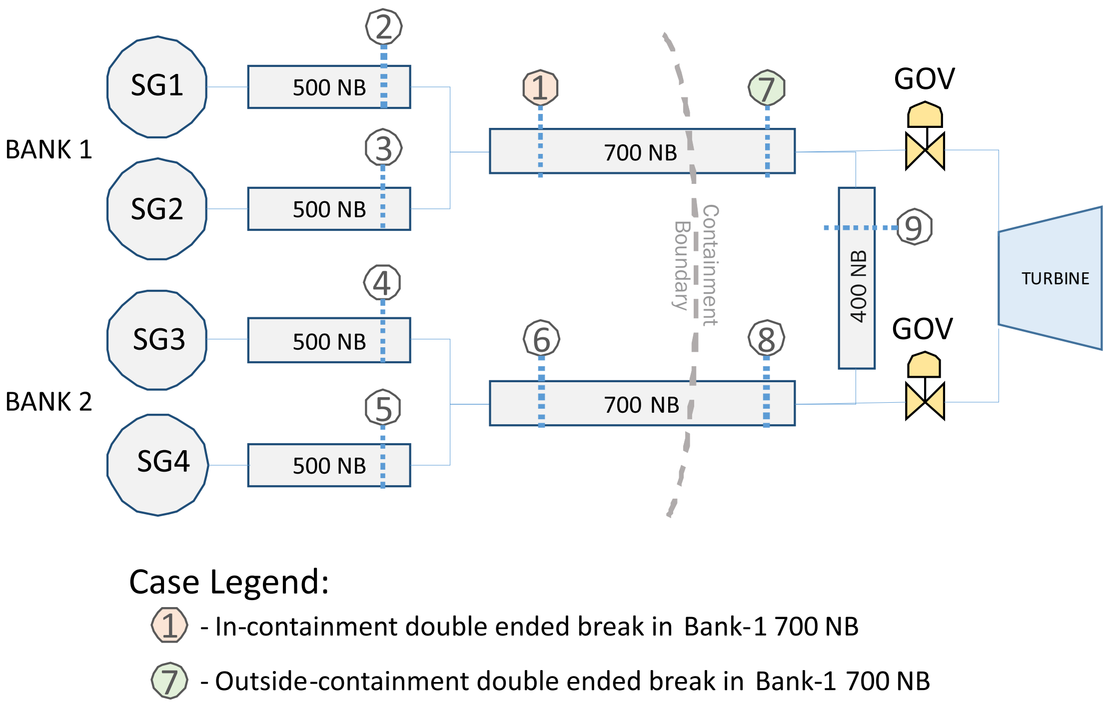

Fig.1: Schematic of main steam lines showing break locations.

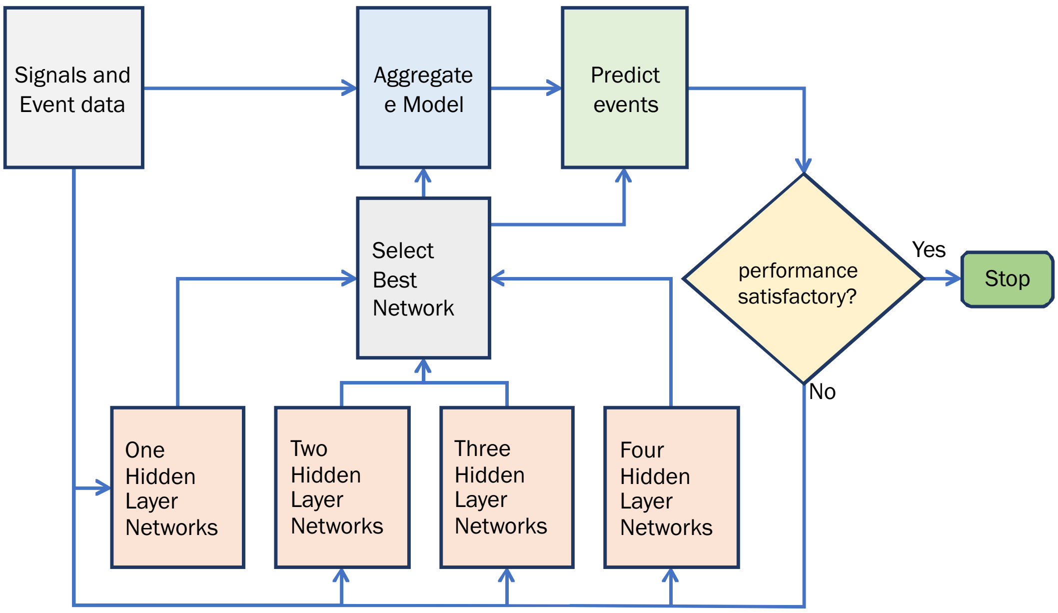

Fig.2: Schematic diagram of ANN approach.

(RIH) side, high log rate signal is a first signal followed by high neutron power, while for breaks at Reactor Outlet Header (ROH) side, low pressure signal is usually the first signal followed by high log rate. RELAP5 and CONTRAN thermal-hydraulic codes have been used to simulate 33 LOCA scenarios of pipe break at RIH and ROH, ranging from 20% to 200% double ended guillotine break.

MSLB scenario has also been modelled using RELAP5 and CONTRAN codes for simulating core and containment thermal-hydraulics for postulated pipe break in 400NB, 500NB and 700NB steam pipelines. Fig.1 shows the simulation carried out for 9 break locations. Transient data for two subsets each of 9 postulated cases with and without availability of Emergency Core Cooling System (ECCS) has been generated. Thus, a total of 18 cases have been analysed covering the possible break sizes, location and availability of ECCS. Transient results for COIS parameters in primary and secondary loops have been used in the development of ANN models.

Model Development

The transient identification can be classified as a pattern recognition problem and neural networks are found to be suitable for such problems. There is no pre-determined criterion for choosing a specific structure of neural network and development of a best-performing network is based on the trial and error approach. The schematic diagram describing the model development approach is shown in Fig.2. Random sets of 1-hidden, 2-hidden, 3-hidden and 4-hidden layer neural networks are generated and a best-performing network from

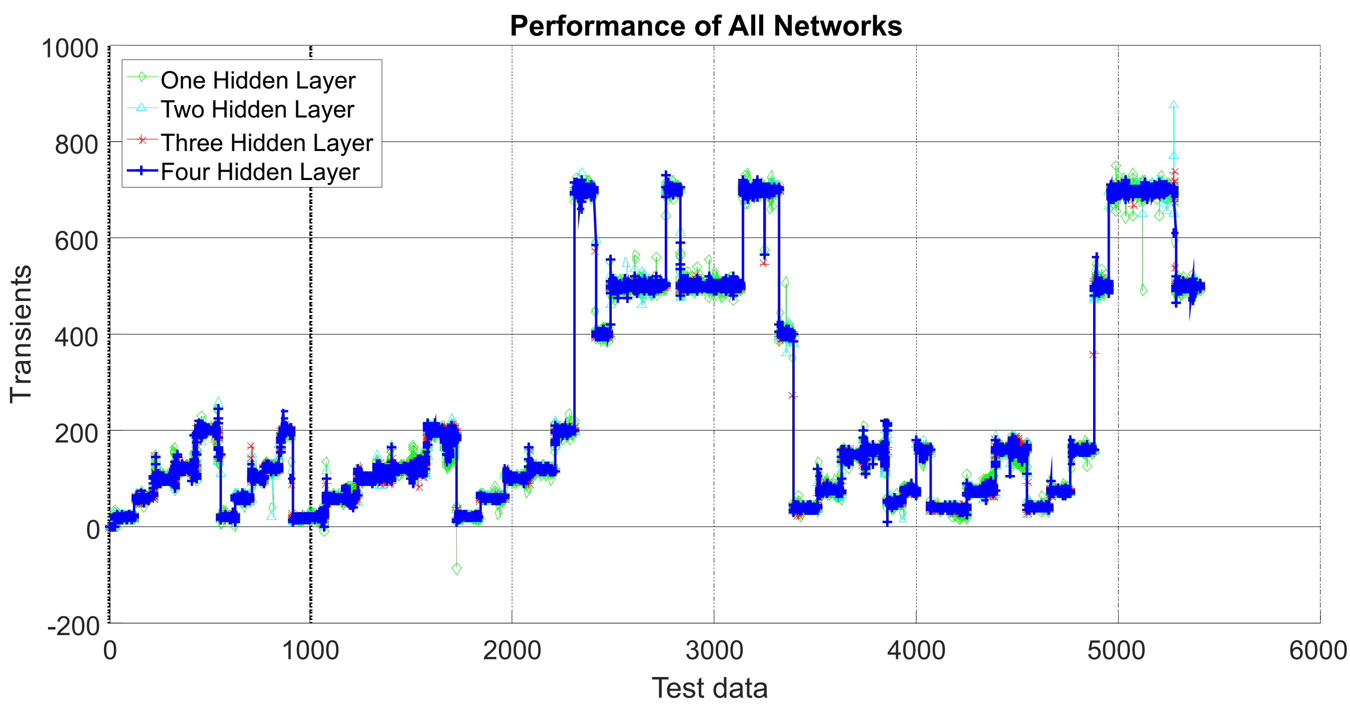

Fig.3: Performance of all networks .

each category is selected based on the lowest Root Mean Square Error (RMSE). Depending on the individual network's performance, a set of best-performing networks will be selected for creating an aggregation model. If the performance of the aggregate model or any individual network is satisfactory then the model development process is terminated. This process is repeated until reasonably acceptable model is evolved.

Training data

Artificial neural networks are widely known as data-driven techniques which rely on a large database of the input signals. In other words, ANNs require large amount of data to learn and recognize a particular input-output pattern. The transient data generated from RELAP5 and CONTRAN codes is randomly split into 70% training set, 15% validation set and 15% test set using the random sub sampling with no replacement method. This creates a balanced training, validation and test sets which are non-overlapping subsets of the transient dataset. The advantage of using a balanced training set is that this would ensure that the trained neural network would make unbiased estimation of different break sizes in the test set. In contrast, a network trained on an imbalanced training set may tend to result in the break size target corresponding to the majority class of the training set which leads to poor generalization of the network. Validation check is performed during the training phase to control the over-fitting. An event is identified by assigning a suitable event identification code in the input file. The final neural network model consists of 45 inputs and 4 output parameters for predicting LOCA and MSLB scenarios.

Performance of neural network

Levenberg-Marquardt Back-propagation algorithm is one of the most efficient and fast converging algorithms[5]. The Levenberg-Marquardt Back propagation algorithm is used for training the networks with the maximum epochs set to 1000 and the learning rate parameter set to 0.001. Various types of 1-hidden, 2-hidden, 3-hidden and 4-hidden neural networks were generated randomly by fixing the minimum and maximum neurons, and also fixing the total number of weights. The termination criterion is either fulfilling the validation checks or reaching to number of epochs or converging to the pre-set performance level (mean square error) which is set to 1e-4. From the performance evaluation study it is found that 3-hidden and 4-hidden layer networks performed well in predicting all the events over the entire dataset with RMSE less than 3. The prediction performance of all the networks for LOCA and MSLB on test data is shown in Fig.3. In order to further improve the prediction rate, a weighted-average aggregation model from these two networks has also been created. It is observed from the results that the networks are able to capture the distinct feature from the training data to distinguish LOCA and MSLB scenarios which share many common process parameters.

Operator Decision Support System

Diagnostic system employs AI model to predict the accident scenario well before the operator action is anticipated. Continuous monitoring of COIS parameters by AI model enables Diagnostic system to predict the evolving accident scenarios in their early stage[6-7]. Whenever an event is detected, this system will display the type of the event, time at which the event has occurred and the relevant process parameters and their values at the time of initiation of the event. In addition, the trend of important process parameters during accident progression is displayed on the operator screen along with relevant EOPs. Currently, Diagnostic system has been set up on high speed distributed computing servers (Intel i7-2600 CPU @ 3.4GHz with 4GB RAM) for fast processing and real-time response. It has been tested successfully for real-time identification of LOCA and MSLB scenarios in 220MWe PHWRs. Fig.4 shows the screenshot of operator screen of Diagnostic system indicating the identified MSLB scenario inside the containment.

The important process parameters and their values in red background colour indicate an abnormal reactor state. The complete details of the identified scenario are displayed at the bottom panel of the screen.

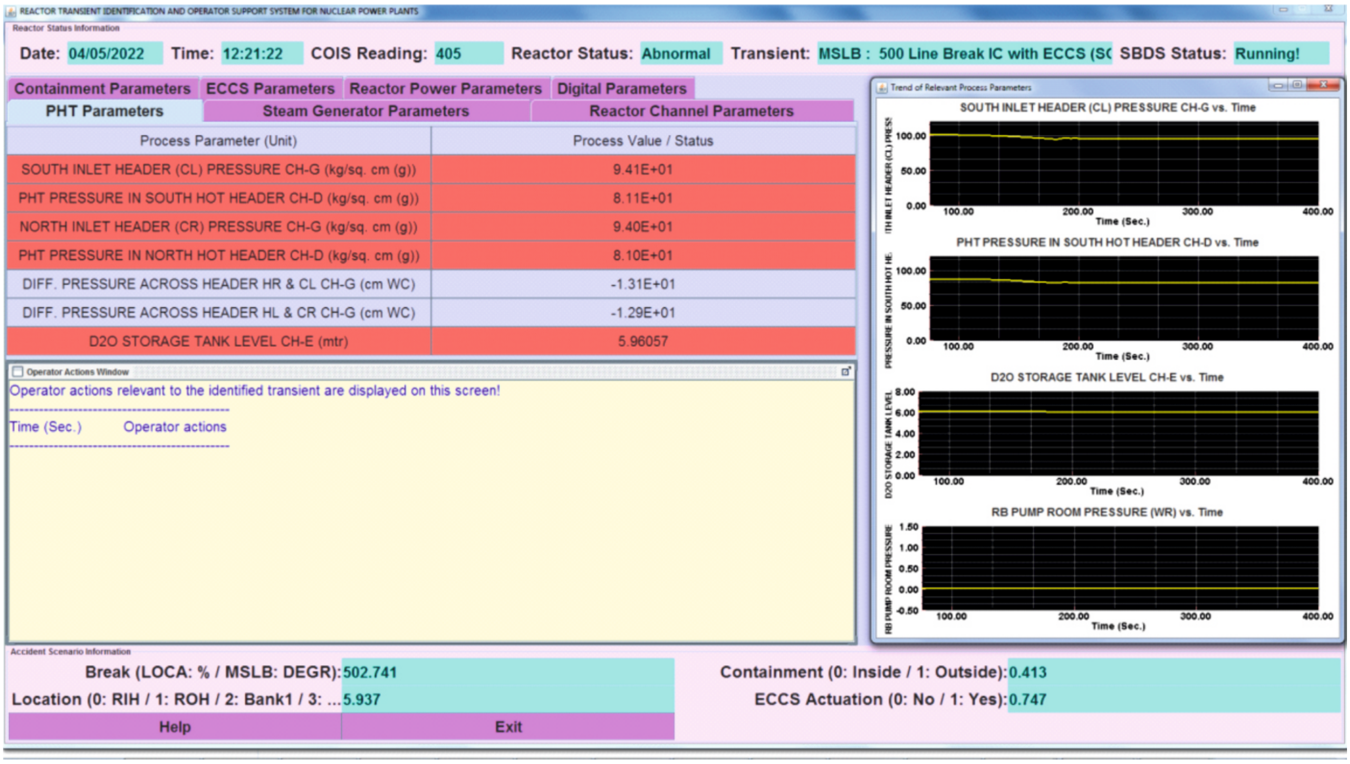

Fig.4: Screenshot of Diagnostic system showing 500NB line break inside containment with the availability of ECCS.

Conclusions

Robust and efficient neural network model has been developed for identification of LOCA and MSLB scenarios in 220 MWe PHWRs. A three-tier learning scheme is followed in developing a single yet efficient ANN model for predicting entire set of LOCA and MSLB transients for real-time application in plant considering the signals from COIS. Blind case validation exercises have been carried out to test the performance of ANN model against generality check. Break size, break location (i.e. distinguishing break inside or outside containment; RIH or ROH, etc.), and also the status of ECCS actuation can be known from the tool. Around 33 LOCA and 18 MSLB scenarios can be predicted from the current version of the Diagnostic system. The Diagnostic system provides confidence to the operator in effective identification and handling of events so that subsequent management of events becomes easier. Diagnostic system can be a useful aid for training the plant operators. This AI based method will reduce dependence on human skill and thus the human reliability factor can improve by reducing stress factor on operator during any event/transient.

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